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Predicting the Corn Basis in the Texas Triangle Area

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Shifting patterns of corn use as a result of the ethanol boom may be causing basis levels to change across the United States, creating the need for methods to predict basis levels in dynamic conditions. This study develops a new and straightforward economic model of basis forecasting that outperforms the simple three-year average method suggested in much of the literature. We use monthly data of the corn basis in the Texas Triangle Area from February 1997 to July 2008. The results show the new model based on economic fundamentals performs better than basis estimates using a three-year moving average.

Key Words: basis, corn, grain marketing, Texas Triangle Area

A central issue for farmers and merchandisers in commodity marketing is forecasting the basis. Tomek (1997) defines the basis as the difference between the cash price and the futures price for a commodity in a specific delivery location and for a specific quality grade. For the purposes of this paper, we follow the norm of real-world traders who use the cash-minus-futures method to calculate the basis (Blank, Carter, and Schmiesing, 1991).

In the United States, corn has long been the crop with the highest total dollar value, but the importance of corn increased even more with the Energy Independence and Security Act of 2007. This legislation mandated the production of at least 36 billion gallons of bio-fuel by the year 2022; an estimated 15 billion gallons of the 36 billion gallon mandate will come from corn-based ethanol. The United States currently has 128 ethanol plants and an additional 85 under construction, located primarily in the grain-surplus Midwestern states (see figure 1). The expanding corn ethanol industry is creating additional local demand for corn that is expected to change basis patterns across the Corn Belt. Additionally, grain-deficit states in the Southeast and Southwest that import corn for livestock feed will likely see changing basis patterns, as they must now compete with the rapidly growing fuel use sector for domestic corn supplies.

As Purcell (1991) summarized, knowledge of basis levels and basis patterns is valuable in virtually any decision involving the use of futures markets as a price risk management tool. Tomek and Peterson (2001) acknowledged the importance

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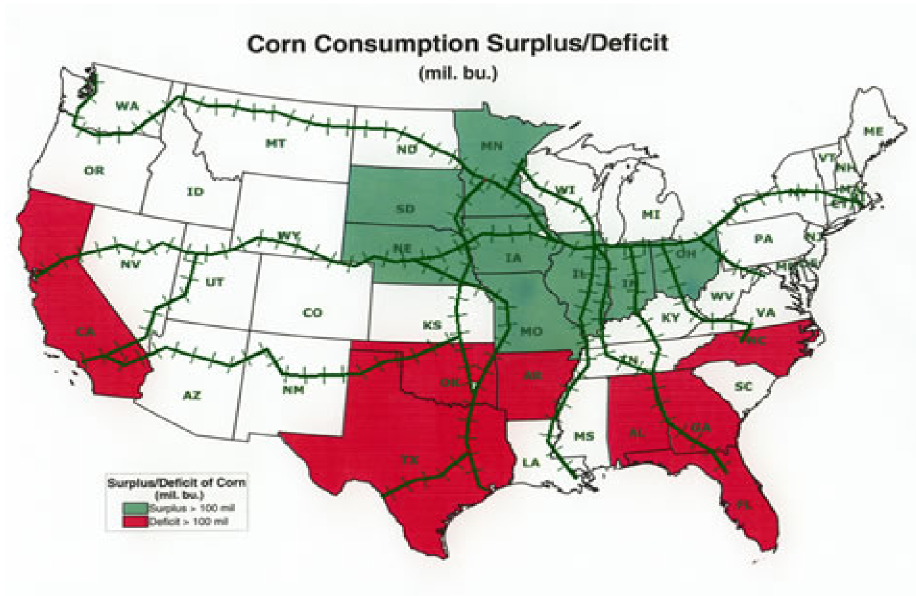
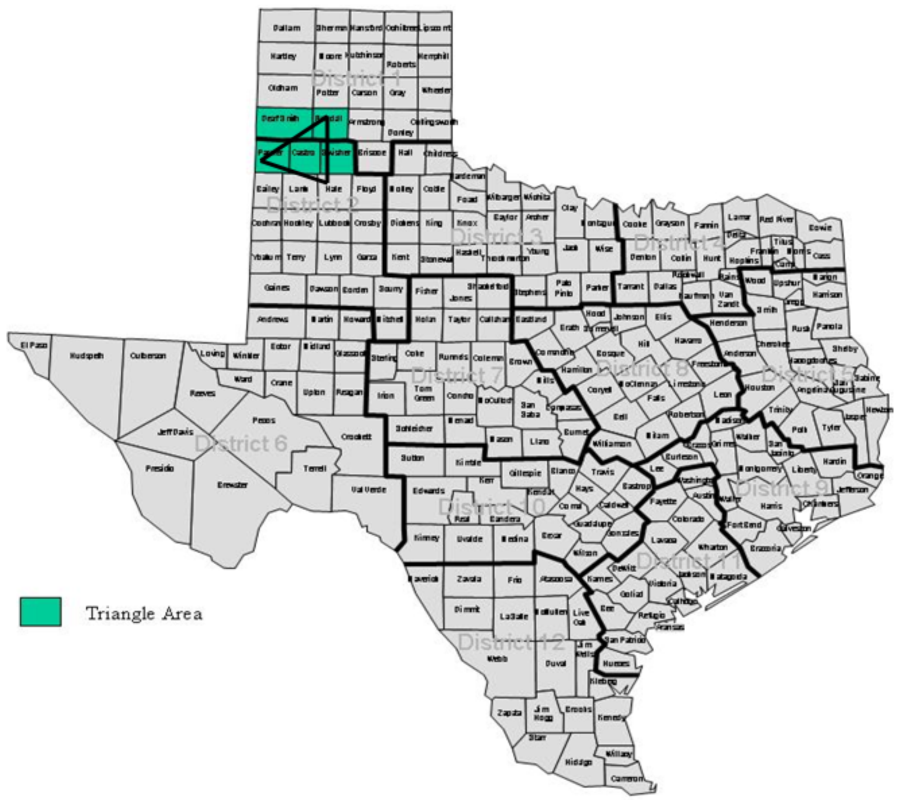


Figure 1. U.S. corn consumption surplus/deficit (million bushels)

of understanding basis relationships and basis risk to hedging effectiveness, calling for additional research to improve our understanding of the basis risk faced by producers. The basis estimation model developed here adds to our understanding of the basis by identifying economic factors that significantly impact basis levels and is responsive to dynamic economic situations, thus improving the accuracy of basis estimates.

The focus of this study is on the Texas Triangle Area, a statistical reporting region of the National Agricultural Statistics Service (NASS) and located in the Texas High Plains (see figure 2). It includes elevators in an area from Plainview to Canyon to Farwell and is comprised of Castro, Deaf Smith, Parmer, Randall, and Swisher counties in the Texas panhandle. The Triangle Area is a leader in Texas corn production and is at the heart of the Texas cattle feeding industry. In addition, White Energy, Inc., of Dallas, Texas, began operation of a 100 million gallon per year (mgy) corn ethanol plant in Deaf Smith County on January 15, 2008. White Energy also operates a 100 mgy corn ethanol plant in adjacent Hale County, Texas. An additional 100 mgy ethanol plant is currently under construction in Deaf Smith County.

It is likely that the pattern of corn basis is undergoing changes given the effects of ethanol policies, increased transportation costs, and volatility in the grain markets more generally. We compare forecasts of the basis, given these dynamic conditions, based on estimated models of the determinants of the basis. Two approaches are compared using both in-sample and out-of-sample data: a purely statistical three-year moving average of the basis, and a model that uses as explanatory variables publicly available data on economic fundamentals that are



Source: http://agecoext.tamu.edu/files/images/maps/Triangle.jpg

Figure 2. Texas Triangle Area

well supported by economic theory. By doing so, this study makes methodological and policy contributions to the understanding of the relationship between grain futures markets in Chicago and local cash markets.

Literature Review

Understanding basis determinants is important to price risk management, yet efforts to produce a simple, practical means to estimate basis have been elusive. The model used by Jiang and Hayenga (1997) includes storage cost, transportation cost, and regional supply and demand variables to explain basis behavior. They employ a number of forecasting techniques for the corn and soybean basis, including a simple three-year moving-average forecast, a structural econometric model, a modified three-year average model, artificial neural networks, seasonal ARIMA time-series models, state-space models, and composite forecasts. They conclude that three-year-average-plus and seasonal ARIMA models are the most practical, are much easier to use than alternative models, and slightly outperform the simple three-year-average forecast. Sanders and Manfredo (2006) also find, in the case of the soybean complex, that the gains from using sophisticated time-series models rather than a simple moving average to forecast the basis are relatively small.

Taylor, Dhuyvetter, and Kastens (2006) compare practical methods of forecasting the basis using current market information of wheat, soybeans, corn, and grain sorghum in Kansas. Using nine different models to forecast the basis, they conclude that, despite the absence of any rule to define the best forecasting method, using the one-year-average basis to forecast the future basis has worked better than long-term averages with some products. The authors also note that to forecast the wheat basis at harvest, the five-year average performs best.

Parcell, Schroeder, and Dhuyvetter (2000) express concern that because some basis forecasting models are so complex, it is difficult to derive economic precepts from real-world situations. Such models are not practically useful. They focus on using variables that are "… observable and measurable occurrences" (p. 532) in an effort to better understand the factors that affect basis variability. An important contribution of the Parcell, Schroeder, and Dhuyvetter model is the significance of market fundamentals in explaining basis behavior. These add information not captured by seasonal variation and lagged basis values. The explanatory variables in their multivariate model explain 85% of the variation in live cattle basis in Colorado, Kansas, and Texas.

As noted by Tomek (1997), considerable research has been conducted on modeling basis behavior, but the number of forecasting analyses is small. It is often challenging to obtain data for all the variables influencing basis behavior; therefore, forecasts of the basis have been made from simple time-series or naïve models. In his analysis, Tomek examines two types of basis models. The first is related to inventories carried over from one crop year to the next. This model uses the cash prices pertaining to a period near the end of the current crop year and futures quotes for the first contract in the new crop year. This basis measures the incentive for carrying stocks from one year to the next. The second model is related to inventories and basis changes within the same year—i.e., changes over a storage interval.

Tomek concludes that while existing price forecasting models are generally poor predictors of futures prices, they might be valuable to individual enterprises as they develop or obtain information not available to others. He also notes that the effect of small or dwindling inventories on prices is much larger than the effect of large or plentiful inventories. This finding suggests inventories should be included among the explanatory variables for the basis.

Examining the factors influencing the corn basis in Illinois, Garcia and Good (1983) argue that the supply and demand of storage should be included as explanatory variables for the basis in addition to the cost of storage and transportation. They assert that small stocks (inventories) or a strong demand for shipments (exports) could strengthen the basis. Based on the conclusions of Garcia and Good, the three sets of variables that influence the basis are cost, stock, and flow factors.

Cross-section data and time-series data are used for their model. They hypothesize that high levels of corn and soybean stocks create a high demand for storage, which in itself creates high price for storage, all else held constant. The high levels of stocks and high cost for storage create a wider basis. Garcia and Good include barge rates, regional dummy variables, monthly dummy variables, and the interest rate to reflect the relationship between costs and the basis. They report that the basis patterns are fairly systematic, finding storage has a strong positive impact on Illinois basis during harvest time and slightly diminishes in other periods. The cost of transportation is important during the off-harvest season but not during the harvest season.

Hranaiova and Tomek (2001) discuss the importance of the timing option on basis behavior. They look at the basis as a function of interest rates, convenience yield, storage cost, time to maturity, and timing option. Their OLS regression estimates show that at day one of the maturity month, the timing option is statistically important and, with convenience yield included, represents about 92% of the basis.

Most previous studies conclude that an averaging method to forecast the basis is the most practical. However, this method is most likely deficient in times when basis patterns may be undergoing fundamental changes. Moving averages in these situations will be slow to capture altered cash-futures price relationships stemming from new economic fundamentals. Here, we compare an alternative method of basis estimation using a few relevant variables from readily available data sources to the traditional moving-average approach. If the new model is seen as providing better estimates of the cash-to-futures price relationship, it will be useful to producers and users of corn in the Texas panhandle in formulating price expectations. It may also provide a foundation for corn producers in other areas who seek a better way of forecasting the basis in their region.

Methodology

Based on economic theory, previous literature, and a goal of keeping the model succinct, seven variables were chosen for their anticipated significance in predicting the Texas Triangle Area corn basis. These variables and their predicted signs are: (*a*) local cash price (+); (*b*) futures price, December maturity (−); (*c*) estimated marketing year ending stocks (−); (*d*) transportation costs (+); (*e*) the basis in a previous time period (+); (*f*) Texas off-farm inventories (−); and (*g*) a harvest dummy.

Local cash price and futures price are included based on the definition of basis, which is defined here as cash price minus futures price. If the cash price increases, all else equal, the basis will by definition increase. This is also included to capture any changes in basis due to the absolute level of prices. If the futures price increases under the same conditions, the basis will decrease. We use the nearby December contract as a proxy for all futures contracts since it is the dominant futures contract for corn marketing in the region under study; all pre-harvest and harvest time pricing in the Triangle Area is based on December futures. In addition, the inclusion of December futures is a precursor of future stocks-to-use ratios in that higher futures prices are an indicator of tighter corn stocks relative to demand, and lower futures prices are an indicator of more ample supplies under the same conditions.

The *Ending Stocks* variable is included following the Kaldor-Working theory of storage because corn is a storable commodity and estimated levels of ending stocks are important measures of supply and demand fundamentals. A *Transportation Cost* variable is included since Texas is a corn-deficit state and corn is imported into Texas from corn-abundant states. This is intended to capture the effect of oil price increases from 2005 to 2008. A *Lagged Basis* variable is added to stabilize the data and to account for serial correlation. A *Texas Off-Farm Inventories* variable is added to capture the effect of local inventories on local basis. A harvest-time dummy variable (*Harvest Dummy*) is added to capture the influence of harvest on the Triangle Area basis. All regressions are run in SAS and predictions are calculated in Excel. The model we propose is given by:

$$\begin{aligned}(1)\quad Basis_t = {} & \beta_0 + \beta_1 Basis_{t-1} + \beta_2 Avg.Cash_t + \beta_3 Avg.Dec.Futures_t \\ & + \beta_4 EndingStocks_t + \beta_5 Transportation_t + \beta_6 TexasOff\text{-}Farm_t \\ & + \beta_7 HarvestDummy_t + \varepsilon_t \\ & \text{for } t = 1, \ldots, 138,\end{aligned}$$

where

- $Basis_t$ is the monthly average of weekly cash grain prices in the Texas Triangle Area (price information gathered on Thursday afternoons after the futures markets close) minus the simple average of daily closing prices in the nearby Chicago corn futures contract (prices roll over prior to the beginning of the month of contract expiration);
- $Basis_{t-1}$ is the basis lagged one period (monthly);
- $Avg.Cash_t$ is the average cash price in time t in the Texas Triangle region;
- $Avg.Dec.Futures_t$ is the average December futures price of corn at time t at the Chicago Board of Trade;
- $EndingStocks_t$ is the projected ending stock of corn reported by the U.S. Department of Agriculture (USDA), updated monthly;
- $Transportation_t$ is the transportation index with a base year of 1985;
- $TexasOff\text{-}Farm_t$ is the inventory data for the Texas off-farm corn reported quarterly; and
- $HarvestDummy_t$ is a dummy variable for the month of October.

The baseline model chosen is the annual three-year moving average of the basis in time *t*, $MA3_t$, suggested by the literature to be the simplest and most practical way of calculating the basis:

(2) $$Basis_t = \beta_0 + \beta_1 MA3_t + \varepsilon_t$$
$$\text{for } t = 1, \ldots, 103.$$

Data

The data for the basis model are readily available. The average cash corn price in the Triangle region is taken from the Texas AgriLife Extension website at Texas A&M University's Department of Agricultural Economics. Futures prices are from the Commodity Research Bureau's *DataXtract*. Corn ending stocks are from the USDA/NASS "Grain Stocks" website. Monthly updates of projected ending stocks are collected from the USDA's "World Agricultural Supply and Demand Estimates." Transportation data is a monthly producer price index for railroad transportation costs, obtained from the U.S. Department of Labor, Bureau of Labor Statistics. Finally, Texas off-farm inventory levels are taken from the USDA's website. The time period for all data is from February 1997 to July 2008. Table 1 reports the descriptive statistics for the variables chosen for this study.

Testable Hypotheses

In our model, the joint null hypothesis is that: (*a*) the following set of economic fundamental variables is significant in explaining the basis, and (*b*) the variable coefficients have the signs predicted by economic theory. It is expected the basis will be:

- Increasing in *average cash price in the Triangle Area* from the identity *Basis* = *Cash* − *Futures*;
- Decreasing in the *average December futures price*, also from the identity;
- Decreasing in the *monthly update of projected ending U.S. stocks* (*inventories*), since higher ending inventories are associated with tight storage conditions that may force cash sales, thus weakening the basis;
- Increasing in *transportation cost* because higher fuel costs imply it is more expensive to bring corn out of grain-surplus regions (i.e., near the par delivery for Chicago Board of Trade futures) to grain-deficit regions such as the Triangle Area;
- Increasing in *lagged basis*, because the basis is (weakly) serially correlated; and
- Decreasing in the *Texas off-farm inventories*, because higher regional inventories depress local cash prices and weaken the basis, consistent with Garcia and Good (1983).

Table 1. Descriptive Statistics of the Variables (February 1997–July 2008)

Variable	Units	Mean	Standard Deviation	Kurtosis	Skewness	Min.	Max.
Basis	$/bu.	0.113	0.090	0.020	−0.353	−0.140	0.330
Lagged Basis	$/bu.	0.115	0.088	0.025	−0.320	−0.140	0.330
Avg. Cash Price	$/bu.	2.752	0.924	6.570	2.447	1.913	7.110
Avg. Dec. Futures Price	$/bu.	2.728	0.941	8.191	2.727	1.890	7.304
Texas Off-Farm Inventories	1,000 bu.	57,523	32,090.19	−1.113	0.069	6,032	115,256
Ending Stocks	mil. bu.	1,489	495.565	−1.042	0.107	673	2,540
Transportation	index	128.4	18.551	−0.048	1.101	111.5	180.3

Note: Sample size $T = 138$.

A dummy variable is included for seasonality (*Harvest Dummy*). Specifically, the seasonality dummy variable takes the value of 1 if it is October (the month of greatest harvest activity in the Triangle Area), and takes the value of 0 otherwise. Diagnostic tests are performed on the data to evaluate the presence of heteroskedasticity and serial correlation. Based on the results of Durbin-Watson and Breusch-Pagan tests, we cannot reject the nulls of no heteroskedasticity and no serial correlation. The estimated coefficient of serial correlation is −0.016, which is not statistically significant at the 5% level of confidence; the Breusch-Pagan LM test value is 7.79, which is smaller than the χ^2 critical value (5 degrees of freedom and 5% level of confidence) of 11.07.

Results and Interpretation

This section presents the results obtained from running corrected ordinary least squares (OLS) regressions on the two principal specifications as well as specifications that exclude one or more insignificant independent variables.

Economic Fundamentals Model

On the first run of the economic fundamentals model, *Texas Off-Farm Inventories* and *Harvest Dummy* were found to be not statistically significant and are excluded from the final regression specification. Exclusion of these two variables does not substantially affect the final RMSE, although both the R^2 and goodness-of-fit values decrease. The parameter associated with *Texas Off-Farm Inventories* is negative but not significant. The sign indicates that the basis weakens as local grain inventories increase. Increasing inventories could be a sign of weakening demand, which could weaken the basis. Increasing inventories might also reflect large grain production in the area or difficulty arranging transportation to move grain out of inventory. Elevators with full bins would not offer price incentives to encourage producers to bring in more grain. Rather, they are more likely to weaken basis bids to discourage short-term grain deliveries. *Texas Off-Farm*

Table 2. Economic Fundamentals Model: Parameter Estimates, Standard Errors, and *t*-Statistics

Variable	Parameter Estimate	Standard Error	*t*-Statistic	*p*-Value
Intercept	−0.0480	0.0372	−1.29	0.1987
Lagged Basis	0.4753***	0.0749	6.35	< 0.0001
Avg. Cash Price	0.1033***	0.0334	3.09	0.0024
Avg. Dec. Futures Price	−0.1446***	0.0322	−4.49	< 0.0001
Ending Stocks	−0.00003**	0.00001	−2.21	0.0287
Transportation	0.0020***	0.0005	4.08	< 0.0001
Dropped (insignificant) Variables:				
Texas Off-Farm Inventories	−0.2104	0.1529	−1.38	0.1710
Harvest Dummy	−0.0075	0.0184	−0.40	0.6867
Model 1 RMSE = 0.0524 $R^2 = 0.6738$				

Note: Double and triple asterisks (**,***) denote statistical significance at the 5% and 1% levels, respectively.

Inventories may not be significant because the data are measured quarterly, which is a lower frequency than the monthly data collected for the other variables, or because local storage capacity relative to total local demand is small.

The *Harvest Dummy* variable has a coefficient of −0.0075 and is not significant. It is therefore dropped from the final regression model. The negative sign of the parameter is consistent with the theoretical prediction that at harvest, the local increase in corn supply depresses the cash price and weakens the basis.

The final results for our proposed "economic fundamentals" model are summarized in table 2. All of the results are reported at the 95% confidence level. The coefficient for the *Lagged Basis* variable is 0.4753 and is significant. The implication is that, all else held constant, if the basis in the previous month is one cent/bushel higher, then the basis in the current month increases by about half a cent. This finding confirms the expectation that the basis is weakly serially correlated. In other words, if the basis for the previous month is getting stronger (more positive), the basis for the next month will continue strengthening, everything else held constant.

The *Average Cash Price* variable is also significant, with a coefficient of 0.1033. If the local cash price in the Triangle Area region goes up by one cent per bushel, the basis will increase by one tenth of one cent, all else held constant. This result is consistent with the basis formula expressed as cash minus futures.

The *Average December Futures Price* variable has a negative and significant coefficient of -0.1446. Again, the sign for this variable is consistent with the basis definition of cash price minus futures price. If December futures prices go up by one cent, then the basis in the Texas Triangle region will weaken by 0.1446 cents per bushel, all else held constant.

The projected *Ending Stocks* variable is statistically significant and negative as expected, but the coefficient is very small. The coefficient associated with one million bushels of ending stocks is -0.00003, implying that it takes a change of one billion bushels in ending stocks to change the basis by 3 cents, ceteris paribus. Current estimated U.S. ending stocks for 2008–2009 are 1.154 billion bushels. It would take a change in projected ending stocks of about 300 million bushels to change the basis one cent. This result is consistent with the theory because higher projected year-end inventories suggest declining demand or increasing supplies and lower cash prices.

At the suggestion of a reviewer, two other specifications are considered to evaluate whether the effect may be nonlinear. First, we use as an independent variable the natural log of ending stocks. The parameter estimate is found to be about −0.04 and significant, suggesting a stronger relationship, but the overall model fit is essentially unchanged, as the R^2 increases only slightly. Second, we consider the inclusion of both the level of ending stocks and also their squared value. The coefficients associated with ending stocks and squared ending stocks are negative and positive, respectively, suggesting a decreasing, convex relationship. However, neither coefficient is significant. Therefore, we conclude that using the natural log of ending stocks is the preferred specification, although using the level of stocks is also acceptable.

The *Transportation Cost* index variable has a positive and significant estimated coefficient of 0.0020. This result is consistent with the fact that Texas is a corn-deficit state and corn is being imported to Texas from other, corn-abundant states. If the transportation index goes up by one percentage point, the basis strengthens by 0.2 cent per bushel, all else constant. Because it costs more to bring corn from other states to Texas, buyers can afford to pay more to local producers rather than transport it from out of state, thereby strengthening the basis.

Moving-Average Model

Our a priori comparison model is a three-year moving average of the basis. However, since the literature review suggests different time periods may provide better results in different markets, we ran basis estimation models using a one-year average, a two-year moving average, a three-year moving average, a four-year moving average, and a five-year moving average of the monthly basis (table 3). The three-year moving-average model had the lowest RMSE while maintaining significance in the independent variable, so our model selection for comparison purposes was confirmed. In the four- and five-year moving-average models, changes in the moving averages had no significant effects on the level of the basis.

To see if a long-term moving average would improve the results of our economic fundamentals model, we added the three-year moving average as an independent variable and ran the model again. The three-year moving average was found to lack explanatory significance (p-value 0.739), the model's RMSE went up (from 0.0524 to 0.0533), and the R^2 went down (from 0.6738 to 0.6410).

Table 3. Comparison of Alternative Basis Models Using Moving Averages (MA): Root Mean Squared Errors, Parameter Estimates of the Independent Variables, Standard Errors, and *t*-Statistics

Model	RMSE	Parameter Estimate, β_1	Standard Error	*t*-Statistic	Confidence Level Pr > | *t* |
One-Year Average	0.0852	0.3941***	0.0849	4.64	< 0.0001
Two-Year MA	0.0895	0.3961***	0.1081	3.66	0.0004
Three-Year MA	0.0823	0.3743***	0.1155	3.24	0.0016
Four-Year MA	0.0744	0.1638	0.1212	1.35	0.1801
Five-Year MA	0.0738	−0.0819	0.1464	−0.56	0.5773

Note: *** denotes statistical significance at the 1% level.

Table 4. Three-Year Moving-Average Model: Parameter Estimates, Standard Errors, and *t*-Statistics

Variable	Parameter Estimate	Standard Error	*t*-Statistic	Confidence Level Pr > | *t* |
Intercept	0.0909***	0.0152	5.99	< 0.0001
Three-Year MA	0.3743***	0.1155	3.24	0.0016
Model 2 RMSE = 0.0823 R^2 = 0.0933				

Note: *** denotes statistical significance at the 1% level.

Full results of the three-year moving-average model are presented in table 4. A comparison of this model to the economic fundamentals model reveals less explanatory power (R^2 of 0.0933 versus 0.6738) and an RMSE that is 38% higher (0.0823 versus 0.0524), a significant difference.

As the above discussion has shown, a basis estimation model that incorporates fundamental supply and demand information provides better accuracy than simple moving averages. This improvement can be observed in figure 3, which compares historical basis information for corn in the Texas Triangle Area with a moving average model and the economic fundamentals model.

Moreover, the accuracy of basis estimation models has economic implications. Consider the case of a grain elevator or merchant purchasing corn from local farmers on cash forward contracts. If the basis is in a weakening trend, as it was from August of 2007 to June of 2008 (see figure 4), the moving-average model is slow to account for this trend. Using the differences in RMSEs between models for calculation purposes, the grain merchant would possibly overestimate the basis in this case by about 3 cents per bushel (0.082 − 0.052). On a 100,000 bushel contract, this information is worth about $3,000.

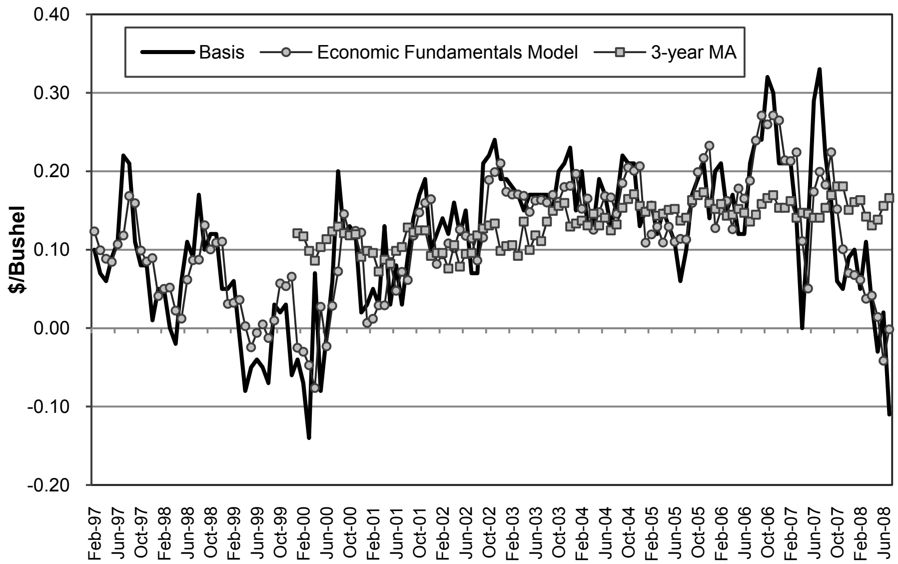


Figure 3. Actual basis, basis estimates from the economic fundamentals model, and basis estimates from the three-year moving-average model (complete sample, February 1997 to July 2008)

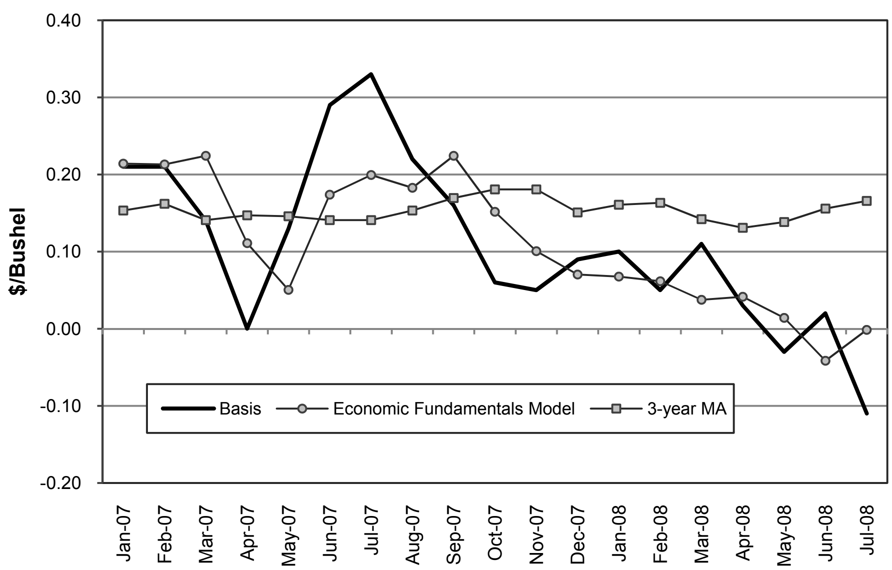


Figure 4. Actual basis, basis estimates from the economic fundamentals model, and basis estimates from the three-year moving-average model (January 2007 to July 2008)

Another way to evaluate the practical implications of the model is to consider a producer's gains and losses from changing basis. For a producer who is long, the commodity gains when the basis rises and loses when it falls. We consider the actual and forecast basis levels for the period August 2007 to July 2008. In each month, suppose the producer uses either the economic fundamentals forecast or the MA(3) forecast, and his or her profit or loss is the unexpected basis change, i.e., actual basis minus predicted basis. Then, the average of the monthly unexpected basis changes is −0.013 for the economic fundamentals model and −0.116 for the MA(3) model. Thus, a producer who forecasts using the economic model will on average lose 1.3 cents a bushel during the 2007–2008 period, while a producer using the MA(3) model will on average lose 11.6 cents a bushel. Note, however, that the results are likely to be sensitive to the period used, so the difference in the performance of the two models may be less pronounced in general.

Although our model is more complex than a straightforward three-year moving-average model, the results clearly suggest that the added difficulty is worthwhile.

Conclusion

A traditional three-year moving average model of the basis does not track changes in the basis as effectively as a relatively simple economic model is able to do. We created a model that uses a few significant variables from easily obtained data sets to explain the basis in the Texas Triangle Area better than a three-year moving average.

Additional research is needed to improve basis predictions to make them more responsive to changes in market fundamentals and the other factors that drive basis levels. For example, the model might be improved if the degree to which futures markets offered full carry-over time were included as an independent variable. Export activity from the ports of Texas may also play a role in determining the grain basis around the state. Specific to the Triangle Area are the construction of new ethanol facilities. New estimates of the basis after plants under construction have come on line and been in operation will provide insight into whether there has been a fundamental shift in the basis due to ethanol manufacture in the area.

By identifying some of the fundamental variables that explain the basis, we can better understand how policy decisions that impact these variables influence local farm prices. Whether it be energy legislation that alters corn demand patterns, fiscal policy that affects the value of the dollar and thus the level of U.S. exports, or programs that provide incentives or disincentives to store grain, the impact may be magnified or mollified at the farm level depending on what it does to the basis.

It is always a challenge to balance potential gains from using more sophisticated methods against the cost of collecting extra data and estimating more complicated models. Although this paper considers a wide range of economically meaningful variables, there remain some explanatory variables that could be further studied to evaluate their contribution to basis forecasting. A natural extension of this work would be to develop a basis model that predicts the basis farther out in the future. Our one-month time horizon validates the importance of fundamental information on basis levels. We now need models that will predict the basis across the growing season and out to the end of projected storage periods.

Understanding the behavior of the basis is essential in grain marketing. It is the means by which the price discovery function of the futures exchange is expressed to producers and users of commodities in specific locations. Recent changes in the fundamentals of corn demand due to ethanol production may have altered the cash-futures relationship in many areas. With a relatively simple model, we can give regional farmers and corn users more accurate predictions of the basis and guidance for future marketing decisions.

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